Populism in a Nutshell: The 2022 Brazilian Election on Twitter

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Introduction

Scholars devoted to populism studies focus on its causes, nature, and consequences. This paper focuses on the second, describing populism in the 2022 Brazilian presidential elections. We ask how populist presidential candidates are by looking at their tweets. The literature suggests that one of the main characteristics of populist leaders is to communicate with their supporters by bypassing traditional means, such as parties (Weyland, 2001). From Getulio Vargas and Juan Peron's radio messages to Hugo Chavez and Rafael Correa's TV shows, populists have used different ways to reach their followers. In the last decade or so, social media allowed populists to exercise unmediated and uninstitutionalized communication more easily. For instance, Bolsonaro talked to his supporters once a week through YouTube livestreams. Yet, the type of communication or relationship populists establish with their followers is not what defines populism. Instead, populism's nature is a set of ideas or a discursive frame that informs how politicians, parties, and individuals understand and portray politics and society.

We apply the ideational definition of populism to tweets by all candidates in the 2022 Brazilian presidential elections. The intersection of social media and elections is a compelling case. On the one hand, politicians rapidly adapted to online reality in order to engage voters and communicate directly with them. On the other hand, it is consensus that populistic appeals tend to be more frequent during campaigns. The literature brings inconsistent results regarding populism on social media, and assessing it has been the subject of a vast debate within social sciences. To overcome time-consuming and limited approaches to rarely mobilized themes in political discourse, as is the case of populism, we develop a machine learning application.

To assess populism on Twitter, we use cutting-edge natural language processing and apply a supervised machine model. Using human-annotated data, we fine-tune the BERTimbau algorithm—the Brazilian version of Google's BERT. This active learning technique allows us to add a new classification layer to the original model to code documents according to the frame of interest. We improve models' performance by hand-coding observations on the threshold and adding them to the training set. After two rounds and a lack of improvement, we adopt a different strategy with undersampling, achieving better results. After training and testing our model, we apply it to the time frame of interest tweets (N = 7374).

Results show that candidates tweet more during the campaign but are not necessarily more populist during this period. On average, presidential candidates tend to be more populist during the pre-campaign phase, slightly moderating their populist tones during the campaign, which drastically drops after the runoff.

The paper begins by discussing the intersection between populism, electoral campaigns, and social media. Second, we discuss methods and techniques, explaining all the steps we took to train the model and the data samples we use. We then explore the results quantitatively. Finally, we draw conclusions considering the limitations of this research.

Populism, Electoral Campaigns, and Social Media

The vast literature on populism has struggled to achieve consensus around its definition since the 1960s. Contemporary efforts to assess populism empirically approach the phenomenon from three main perspectives: the political-strategic (Weyland, 2001), the political-cultural (Ostiguy, 2017), and the ideational (Mudde, 2004) approaches. Although they disagree on what is populism's nature and definitional attributes, the opposition between the people and the elite is at the core of all these approaches (Hawkins and Kaltwasser, 2018; Ostiguy et al., 2021; Pappas, 2012).

We side with the ideational approach. Through this lens, populism is a set of ideas that morally divides society and politics into two antagonistic groups: the pure people and the corrupt elite (Hawkins, 2009; Mudde, 2004). Such an understanding of politics implies a Manichean worldview that assigns a moral tone to every issue, no matter how narrow it is (Hawkins and Kaltwasser, 2018). Populists also claim that politics should be an expression of the people's general will (Mudde and Kaltwasser, 2017) and present themselves as the only legitimate representative of the people once they can understand what this general will is (Müller, 2016). From that, we have a few corollary elements. For instance, populists usually give a cosmic proportion to every political dispute and contend for systematic changes (Hawkins, 2009).

Although we do not understand populism as a political strategy to achieve and exercise power (Weyland, 2001), we acknowledge that campaigns are ideal periods to measure populism in political discourse. Even authors within the ideational school expect politicians to make more populist appeals during campaigns (Mudde and Kaltwasser, 2017). Considering that their communication on social media has fewer constraints than institutional ones, the combination of electoral campaigns and social media tends to be a moment and place where one expects the level of populism to be higher than in official pronunciations and electoral manifestos. Brazil is already known for its high personalist electoral connection (Ames, 2002; Samuels, 2000). The advent of online campaigns makes it even more salient once candidates can communicate directly to their followers, which they promptly do (Klinger and Svensson, 2015; Zamora-Medina and Zurutuza-Muñoz, 2014). Such a communication style increases the proximity between candidates/parties and their followers, even though one should not generalize the statement (Graham et al., 2013). In this paper, we measure populism on Twitter during the 2022 Brazilian presidential campaign, looking at all presidential candidates on Twitter accounts.

Online campaigns received great attention from scholars for different reasons. Research demonstrates that during the 2011 and 2013 Norwaigean elections, political elites figured as the main actors using Twitter, although outsiders increased their use of the tool politically (Larsson and Moe, 2014). Studies show that a negative campaign has a greater impact than a positive one, especially when the attacker is also under criticism (Ceron and d'Adda, 2016). Scholars also analyze how different candidates campaign through Twitter, showing that during the 2016 US presidential campaign, Hilary Clinton maintained civility and politeness, while Donald Trump explored social media amateurish and unprofessionally, portraying himself as a counter-trend in political communication (Enli, 2017). Considering the same case, Francia (2018) shows that Trump dominated the unpaid media market during the 2016 elections, although no evidence can support explanations of his victory as determined by it. Twitter political usage likewise cannot predict victory in primary elections (Murthy, 2015). Studies on Brazilian elections show the spreading of misinformation related to the electoral process on Twitter in 2018 (Ruediger et al., 2020) and a similar pattern in 2022, with fraud allegations and actors advocating for printed ballots (Ruediger et al., 2022).

As populist success means not only electoral success but also their capacity to settle the agenda, political gains from using Twitter during a campaign can also be thought of in terms of agenda-setting. Evidence on that is inconsistent. On the one hand, studies suggest that this is not the case once content on social media does not travel to the traditional communication means and does not impact the main issues of campaigns (Skogerbø and Krumsvik, 2015). On the other hand, findings from the 2017 Austrian campaign show that Twitter enhances parties' capacity to settle the agenda (Seethaler and Melischek, 2019). Whether the effects of political Twitter use are yet to be determined, its consequences on political communication seem clear. These consequences crosscut a few research fields, but their impact on political communication, politeness, and civility is straightforward. This behavior disregards patterns, tacit norms, and rules regarding how political communication should happen, i.e., respectfully and decorously (Habermas, 1996). Not surprisingly, many politicians responsible for that are populists.

On social media, populists not only attack political elites but are more likely to assault and shame traditional media accounts (Jacobs et al., 2020). In Latin America, populist presidents use Twitter to harass journalists, social media users, and citizens (Waisbord and Amado, 2017). Scholars investigate multiple aspects of populist discourses on social media. Findings indicate that extreme and opposition parties show higher levels of populism in Western European democracies (Ernst et al., 2017), stressing all elements of the concept, such as people-centrism, anti-establishment discourse, a notion of a reified will of the people, and a "us" versus "them" logic (Engesser et al., 2017). These studies also reveal the latent nature of populism, as the analyzed cases utilize elements of the concept in a fragmented fashion. However, one should be cautious when taking part as a whole. Scholars suggest that the elements - people-centrism, and anti-elitism - at the core of the definition should exist concomitantly for a case to be positive for populism (Rooduijn and Pauwels, 2011). While the exclusive presence of the former should be taken as demoticism (March, 2017), the latter indicates anti-establishment and not necessarily populism (Pytlas, 2023).

Evidence from Latin America shows that populist and non-populist presidents use Twitter similarly (Waisbord and Amado, 2017). These findings challenge the idea that maintaining close contact with constituents through social media characterizes populist leaders in particular. Only a few studies focused on the Brazilian case, and they are notably interested in Bolsonaro (Cassell, 2021; Moraes, 2023). Moraes (2023) shows Bolsonaro's populism on Twitter mainly relates to attacks on the political left and topics such as economy and technology, democracy and liberties, environmental issues, and a Christian agenda. Despite the multiplicity of empirical work on supply-side populism on Twitter, rare efforts to identify Brazilian politicians' populist rhetoric on the platform exist. Presidential candidates have regularly used social media platforms to communicate with the public. Considering that Brazil is among the top five users of Twitter (Shephard, 2024) and more than 42% of the population uses social media daily to get political information [1], one can assume candidates will use social media to engage more voters. Therefore, this paper looks at this exciting combination of populism, campaigns, and social media and addresses who the most populist candidate on Twitter is in the 2022 Brazilian elections. The following section discusses our data and techniques to assess populism on Twitter.

[1] According to the 2022 wave of the Brazilian Electoral Study.

Methods and Data

There are many methods one can use to assess populism. The literature explored a few, such as holistic grading (Hawkins, 2009), classic and computerized content analysis (Rooduijn and Pauwels, 2011), unsupervised (Núñez and Strasberg, 2023), and supervised machine learning (Bonikowski et al., 2022; Cocco and Monechi, 2022).

Holistic grading and classic content analysis rely on human coding. Although case- and context-sensitive, these are time-consuming, limiting the amount of text one coder can analyze in a particular time frame. Automated content analysis overcomes the time-consuming exercise of hand-coding. However, it lacks context sensitivity because it relies on a dictionary approach and consists of a list of terms and their occurrence in the text (Bonikowski et al., 2022). A particular shortcoming is the potential diverse meaning the same term can hold (DiMaggio, 2015). It is no surprise that populism's shape and facade depend on the context. Consequently, the same word can signify different things in different contexts and even have distinct meanings in the same context. Unsupervised machine learning applications' popularity in social sciences has grown in the last decade. Topic modeling and word co-occurrence networks followed by clusterization try to identify latent topics in large text corpora, determining patterns. Word embeddings, "the representation of terms or documents as dense vectors in multidimensional space" (Bonikowski et al., 2022, p. 1741), attribute similar meanings to different terms according to their geometrical proximity. While useful for persistent themes and specific language elements, they do not help in assessing populism once the nature of the phenomenon in the language is complex to identify and measure.

Supervised machine learning involves using a set of classified documents to train a classifier (Nelson et al., 2021). The goal is to identify patterns in the data that differentiate between categories of interest (Bonikowski et al., 2022). Once trained, the classifier applies these learned classification rules to unlabeled texts. We follow Bonikowski et al. (2022) and use pre-trained neural language models. Since we are interested in text in the Portuguese language, we depart from BERTimbau (Souza et al., 2020), the Portuguese version

Table 1: Steps for labeling data, fine-tune BERTimbau, active learning, and data classification

Step	Description
1	2290 tweets were randomly sampled from the total corpus (30k).
2	Each tweet was annotated by two independent annotators, with a third coder resolving disagreements.
3	Iteration of the first model with a training-testing (70%/30%) split.
4	K-fold cross-validation with 5 folds for better model selection, with 80% of each fold assigned for training and 20% for testing.
5	Best model was retrieved based on the F1 score for class 1 (Model 2).
6	From the previous test, we select a new sample of tweets with a probabiility range between 0.3 and 0.7. Two coders annotated these observations and a third one resolved disagreements
7	The new annotated sample was added to training settings, resulting in a slight improvement of the F1 score for class 1 (Model 3).
8	A second annotation round with 150 tweets with predicted probabilities between 0.4 and 0.6. Two annotators coded them, and a third one solved divergencies, resulting in no improvement in the next training round.
9	Worse results observed after training with new data.
10	We trained a fourth model using all samples, with an undersampling technique to balance the classes with 30% of populist tweets and 70% of non-populist tweets. With an 80-20 train-test split, we achieve a F1 score equals 0.67 for class 1 (Model 4)
11	Model 4 was applied over tweets from our data frame of interest, labeling as populist those with predicted probabilities equal to or greater than 0.5.

of BERT (Bidirectional Encoder Representations from Transformers). This model is trained over 17.5GB of data, representing 3.53 million text documents. We fine-tune the model according to our necessity: the classification of tweets by politicians. To teach the model our category of interest - populism - we manually code a representative sample (N= 2290) of our population of tweets (N = 30276). We then start an iterative active learning process to improve the model performance until we observe no improvement. Let us unpack the procedures.

The first step is to prepare the data following standard steps in text analysis. We eliminate emojis, links, and special characters. Second, two coders classify the sample for populism. A third coder resolves disagreements. To check whether coders have a shared understanding of populism, we test the intercoder reliability through the Krippendorff alpha test (Krippendorff, 2004). With α equals 0.94, acceptable for social sciences, we proceed to the active learning step.

First, we trained a model to check BERTimbau feasibility. This model was trained on a dataset of 2290 tweets in three epochs, divided into two-thirds for training and one-third for testing. As Table 2 shows, this model's performance was unsatisfactory, particularly for the positive cases class. We then adopt a k-fold cross-validation training approach to mitigate the impact of class imbalance. We divided our sample into five random sets with the following proportion for each split: training and validation (80%) and testing (20%). We then ran these five splits over our sample of interest - tweets from June 16, 2022, when the pre-campaign began, to December 12, 2022, when the Brazilian Supreme Court acknowledged Lula da Silva's victory - and retained the optimal model based on the f1-score capability to predict classification probabilities (Model 2). From the model with the best performance, we select tweets with high entropy - those with classification probabilities close to 0.5 - and two coders annotate them with a third one resolving controversies. We add these hand-coded paragraphs to the training set and repeat training, validation, and testing steps. After iterating the process two times, we observed no improvement (Model 3).

Table 2: Models Performance

	Model 1 (no k-fold)		*Model 2 (k-fold)*		*Model 3 (k-fold with improvements)*		*Model 4 (k-fold with undersampling)*	
Candidate	*Not Populist*	*Populist*	*Not Populist*	*Populist*	*Not Populist*	*Populist*	*Not Populist*	*Populist*
Precision	0.97	0.30	0.95	0.54	0.96	0.54	0.91	0.57
Recall	0.97	0.34	0.95	0.46	0.95	0.59	0.77	0.81
F1	0.97	0.32	0.95	0.51	0.95	0.57	0.83	0.67
F1-Macro	0.65		0.71		0.73		0.75	
Accuracy	0.87		0.91		0.91		0.78	
Test	760		468		468		249	

Since we had no improvement after two rounds of annotation, we adopted a different strategy. We split the sample into two random sets with the same proportions of training and validation (80%) and testing (20%). Since populism is a rarely-occurring theme (Bonikowski et al., 2022), we adopted a quasi-balanced undersample strategy (Mahmoudi and Salem, 2023), generating a sample with 30% of populist tweets and 70% of non-populist observations. This final model shows a slight improvement in its predictive capability for positive cases and a subtle deterioration for negative ones (Model 4). Model 4 has lower precision for non-populist tweets but the best recall and precision for positive cases, achieving the best f1-macro of all four models. We opted for model 4, considering its higher capacity to predict probabilities for class 1—populism. Even though it is a trade-off once the likelihood of correctly coding non-populist tweets declines, the precision, recall, and F1 scores are higher for populist tweets. F1-Macro also shows a harmonic average considering all metrics mentioned above, also indicating a slight improvement of the model. That said, we acknowledge that improvements are necessary, which can be done by training the models over larger text corpora or other sampling strategies. To assess the level of populism in tweets by presidential candidates on Twitter, we apply Model 4 to tweets from our time frame of interest (N = 7374).

The data we use to train our model are tweets by the 2022 elections presidential candidates from 2012 to 2023. Although we train and validate our models considering the entire period, we test them over our sample of interest, which we split into three moments:

pre-campaign, between mid-June and mid-August; campaign, between August 16 and the runoff, on October 30; and after elections, from the day after the runoff to December 12, when the Supreme Court officially acknowledge the winner's presidency. These different moments allow us to check how populism varies before, during, and after the electoral campaign. The results of the model indicate what is the probability of each tweet being populist. We consider populist observations with a probability equal to or greater than 0.5.

Table 3: General Results: Model and Samples

	N of Tweets	**Populist**	**Not Populist**
Total	30276 (100%)	24516 (19%)	5760 (81%)
Period of Interest	7374 (100%)	5616 (24%)	1758 (76%)
Sample	2290 (100%)	242 (11%)	2048 (89%)
Improvements	220 (100%)	42 (19%)	178 (81%)
Final sample	2510 (100%)	284 (11%)	2226 (89%)

Source: Made by the authors with data from Twitter.

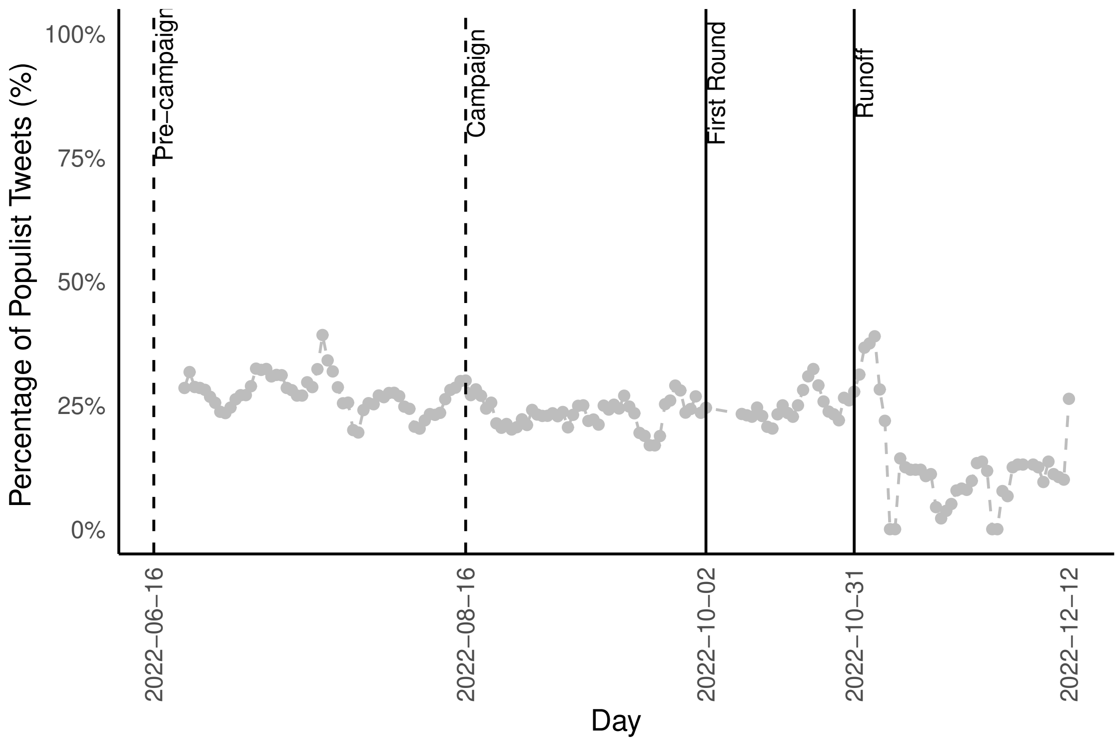
Table 3 shows the general results for populism for different samples. Although one could question the choice for Model 4, we stress that the model (Final Sample) has similar results for populism as the annotated (Sample) data, whose level of reliability is exceptionally high. When running the final model over the time frame of interest (Period of Interest), findings follow theoretical expectations that levels of populism tend to be higher in the lead-up to campaigns. In the subsequent section, we explore our findings.

Results

Figure 1 shows the moving average level of populism considering all candidates. There is only a slight variation between the pre-campaign and campaign moments. By the end of the runoff campaign, there was an increase in the level of populist tweets by Bolsonaro and Lula da Silva, which dropped and then rose again, continuing to rise for a few days after election day. One thing is worth mentioning, however. After the results confirmed

Lula da Silva's victory, the then-president Jair Bolsonaro stopped tweeting for the rest of the analyzed period. Therefore, data after the runoff vertical line stems only from Lula da Silva's account.

Figure 1: Moving Average Level of Populism on Twitter: All Candidates



Note: After the first round, only Lula da Silva and Jair Bolsonaro are considered.

Source: Made by the authors with data from Twitter.

Table 4 shows results for each candidate in different time frames. Considering the entire period of analysis, Felip D'Avila (44.7%), running for the New Party (NOVO), appears as the most populist. He is followed by the Brazilian Labor Party (PDT) candidate Ciro Gomes (43.4%). The third place is Vera Lucia (41.4%), the candidate for the Unified Workers Socialist Party (PSTU). The frontrunners - Jair Bolsonaro, running for the Liberal Party (PL), and the Workers' Party (PT) leader, Lula da Silva - come in fourth and sixth place, with 26.1% and 20% of populist tweets, respectively. The other five candidates split into two groups, three showing high populism and the other two making few, if any, populist appeals.

During the campaign, Gomes was the most populist, followed by D'Avila and Lucia. While the former's level of populism increased during this period, the other two proportions of populist appeals declined. Although Bolsonaro's level of populist tweets increased by 5.3 percentual points, he keeps the fourth place. Lula da Silva appears as the seventh more populist during the campaign.

Table 4: Results for Different Time Frames

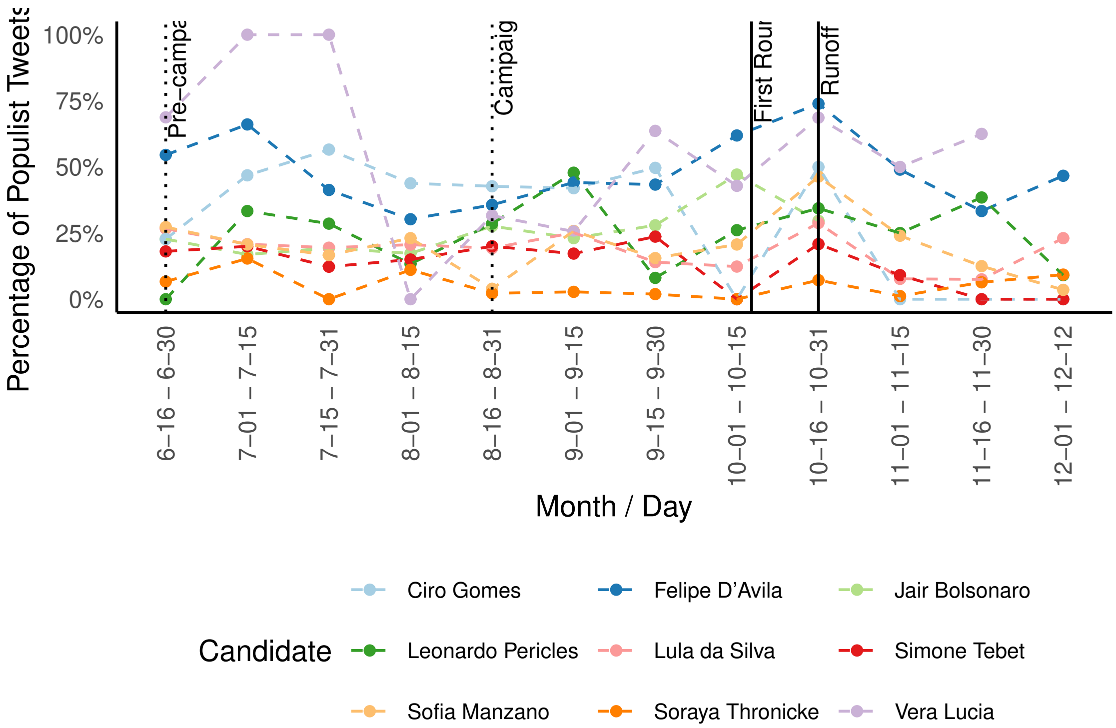
	Entire Time Frame		**Pre-Campaign**		**Campaign**		**After Runoff**	
Candidate	*N of Tweets*	*Populist*	*N of Tweets*	*Populist*	*N of Tweets*	*Populist*	*N of Tweets*	*Populist*
Ciro Gomes	831	43.4%	355	42.8%	471	44.4%	5	0%
Felipe D'Avila	615	44.7%	178	48.9%	343	42.9%	94	43.6%
Jair Bolsonaro	664	26.1%	288	19.1%	376	31.4%	0	0%
Leonardo Pericles	258	24%	42	21.4%	184	24.5%	32	25%
Lula da Silva	1768	20%	401	21.7%	1196	20.6%	171	12.3%
Padre Kelmon	40	0%	2	0%	36	0%	2	0%
Simone Tebet	644	17.5%	230	16.1%	365	20.5%	49	2%
Sofia Manzano	1172	19.6%	334	21%	695	20.7%	143	11.2%
Soraya Thronicke	1008	3.5%	52	7.7%	649	2.9%	307	3.9%
Vera Lucia	374	41.4%	20	70.9%	344	39.2%	10	60%
Total	7374	23.8%	19028	27.1%	4659	24.4%	12.9	12.9%

Source: Made by the authors with data from Twitter.

Figure 2 displays how the level of populism change over time for each candidate. While the y-axis portrays the percentage of populist tweets, the x-axis shows semi-monthly periods. Vertical lines in the graphic mark important time frames: pre-campaign, campaign, the short period between the first round and the runoff, and finally, the 43 days between the runoff and December 12, when the Supreme Court appoints Lula da Silva as the elected president. This figure raises a few trends alongside Table 4. It draws attention to the fact that Gomes, D'Avila, and Lucia use populism consistently throughout the entire data frame, although Gomes's number of tweets falls drastically after the runoff. All candidates tweet more during the campaign. Although at different levels, Lula, Gomes, and Sofia maintain the proportion of populist tweets, even though they post more than other periods. If one assumes that the candidates' ideology is equivalent to their parties' (Bolognesi et al., 2023), findings confirm that populism is not exclusively right- or left-leaning but rather exists all over the ideological spectrum.

Finally, Figure 3 focuses on the two candidates that contested the runoff. During the

Figure 2: Level of Populism in Candidate's Tweets

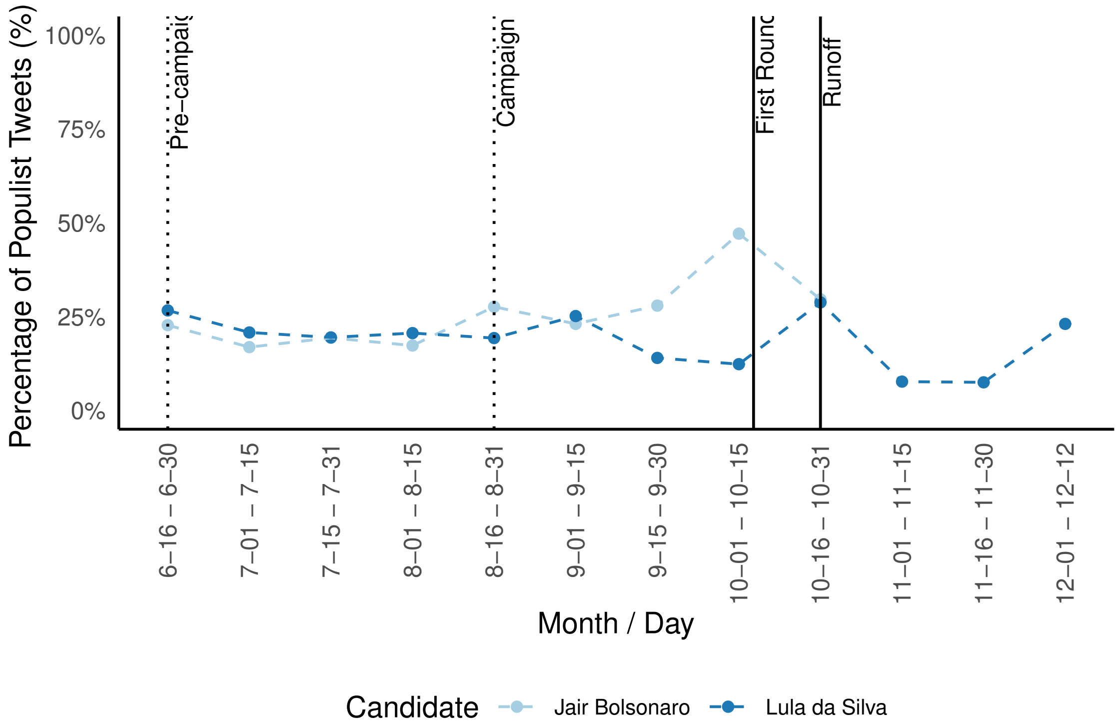


Note: After the first round, only Lula da Silva and Jair Bolsonaro are considered.

Source: Made by the authors with data from Twitter.

pre-campaign period, Lula da Silva and Bolsonaro presented similar levels of populism on Twitter. During the first round of the campaign, Bolsonaro's level of populism gradually increased, while Lula da Silva moderated his tone. An opposite pattern occurs during the runoff campaign, with Lula da Silva becoming more populist than previously and Bolsonaro moderating his level of populism. Why they behave like that escapes the aims of this article, but one can speculate that Bolsonaro's behavior stems from his second place in polls, as a movement to alleviate the public opinion impression of him as an extreme candidate. In turn, Lula da Silva intensified his attacks on the incumbent, advocating for change. Lula da Silva's level of populism declined after the runoff to slightly increase again, when close to his indication by the Supreme Court. The rise of Lula da Silva's populism in the aftermath of the elections coexists with Bolsonaro's silence about the process after discrediting the

Figure 3: Level of Populism in Lula da Silva and Jair Bolsonaro's Tweets



Note: After the first round, only Lula da Silva and Jair Bolsonaro are considered.

Source: Made by the authors with data from Twitter.

electoral process for years and refraining from conceding defeat.

In sum, the results show that the candidates tend to post more during the campaign, even though the period pre-campaign is slightly more populist than the campaign itself. Although most candidates post more populist tweets campaign in absolute terms, the proportion of populist tweets declines once populism dilutes among other themes. Finally, it is symptomatic that both the number of tweets and the average level of populism dropped after the elections.

Conclusion

Table 5: Scores

State	Coder 1	Coder 2	Average
California	1.0	1.3	1.15
Florida	1.6	1.4	1.5
Georgia	1.4	1.2	1.3
Iowa	0.5	0.3	0.4
Michigan	1.6	1.5	1.55
Nevada	0.4	0.4	0.4
New Hampshire	0.8	1.1	0.95
North Carolina	1.6	1.6	1.6
Ohio	1.4	1.6	1.5
Pennsylvania	1.2	0.8	1.0
South Carolina	1.1	1.0	1.05
Tennessee	1.2	1.2	1.2
Texas	1.4	1.2	1.3
Virginia	0.6	0.7	0.65
Wisconsin	0.9	1.2	1.05
Super Tuesday	0.3	0.5	0.4
Trump's Final Score			1.0625

Table 6: Trump's Populist Score by Speech

	Scores		
State	*Coder 1*	*Coder 2*	**Average**
California	1.0	1.3	1.15
Florida	1.6	1.4	1.5
Georgia	1.4	1.2	1.3
Iowa	0.5	0.3	0.4
Michigan	1.6	1.5	1.55
Nevada	0.4	0.4	0.4
New Hampshire	0.8	1.1	0.95
North Carolina	1.6	1.6	1.6
Ohio	1.4	1.6	1.5
Pennsylvania	1.2	0.8	1.0
South Carolina	1.1	1.0	1.05
Tennessee	1.2	1.2	1.2
Texas	1.4	1.2	1.3
Virginia	0.6	0.7	0.65
Wisconsin	0.9	1.2	1.05
Super Tuesday	0.3	0.5	0.4
Trump's Final Score:			**1.06**

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